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Do shocks permanently change output? Local persistency in economic time series

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"Do Shocks Permanently Change Output? Local Persistency in Economic Time Series"

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Abstract

While it is recognized that output fluctuations are highly persistent over certain range, less persistent results are also found around very long horizons (Conchrane, 1988), indicating the existence of local or temporary persistency. In this paper, we study time series with local persistency. A test for stationarity against locally persistent alternative is proposed. Asymptotic distributions of the test statistic are provided under both the null and the alternative hypothesis of local persistency. Monte Carlo experiment is conducted to study the power and size of the test. An empirical application reveals that many US real economic variables may exhibit local persistency.

1 Introduction

Since the influential article by Nelson and Plosser (1982), hundreds of economic time series have been examined by unit root tests and empirical evidence has accumulated that many economic and financial time series contain a unit root. However, as argued elsewhere (see for example Kwiatkowski et al., 1992), many standard testing procedures consider the null hypothesis of a unit root which ensures that the null hypothesis is accepted unless there is strong evidence against it. Indeed, different results have been obtained from other approaches.

While it is recognized that many economic time series are persistent, less persistent results are also found around very long horizons (see, e.g., Beaudry and Koop 1993; Hess and Iwata 1997; Koenker and Xiao 2002), indicating the existence of "local persistency" in economic time series. For example, output fluctuations may be persistent over a long range of time, but not forever and will eventually disappear (Conchrane, 1988).

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In recent ten years, a large amount of literature have emphasized that many economic time series are better characterized by a process with root near unity rather than an exact unit root. In effect, Chang and Lai (1998) claim that most of real exchange rates of the G-7 countries has root near unity. Lanne (2000) claims that the dynamic of interest rates are better characterized by a process with a root near unity rather than a process with an exact unit root. Dutkowsky and McCoskey (2001) show that near-unit roots are also present in the spread between Federal Funds rate and the discount rate during the post-1987 period and they use this fact to show that structural restrictions are compatible with stationary borrowing and a spread with root near unity.

The simplest local to unity model is a triangular array for a time series y_i of the form

$$y_i = \alpha y_{i-1} + u_i, \quad \alpha = 1 + \frac{c}{n}, \quad i = 1, ..., n \tag{1}$$

with iid$\left(0, \sigma^2\right)$ innovations u_i. While the autoregressive coefficient $\alpha \to 1$ as $n \to \infty$, it is apparent that for any given sample size n in (1), the model accommodates a wider range of autoregressive coefficients as the localizing parameter c varies, including both stationary $(c < 0)$, explosive $(c > 0)$ and unit root $(c = 0)$ possibilities. This flexibility has helped to make the model popular in studying economic time series for which roots near unity are considered highly plausible but roots at unity are considered too restrictive. However, in the traditional local to unit root model, shocks are still permanent and can not capture the feature of local persistency.

In this paper, we use a new time series model recently proposed by Phillips et al. (2001) to capture local persistence. This new formulation of local to unity model offers more flexibility than the traditional model (1). The new model leads to a class of different limit processes beyond simple diffusions and also provides a more complete interface between $I(0)$ and $I(1)$ models and between $O(\sqrt{n})$ and $O(n)$ asymptotics. We call this model a block local to unity model. This model generates processes with roots near unity and includes local persistency as a general case. By proposing a statistical test that can be used to detect the presence of local persistency in economic time series, this paper aim to provide a first step of study on locally persistent processes.

This paper is organized as follows: Section 2 presents the stochastic block local to unit process, developed by Phillips et al (2001). The locally persistent process is compared with the fractionally integrated process, which is a related but different process. The behavior of the impulse response function is also investigated in section 2. In section 3, we introduce a test through which we test the null hypothesis of stationarity against local persistency of near unit root processes and derive its asymptotic distribution under the null and alternative hypothesis**.** Section 4 presents some results of the Monte Carlo experiments. An empirical study on the presence of local persistency in some US time series is conducted in Section 5. Section 6 concludes.

A word on notation. We will use the symbols " $\Rightarrow$ ", " $\to$ " and " $:=$ " to signify weak convergence, convergence in probability and equality in distribution, respectively. Following the standard stochastic order of magnitude notation, we write $X_n = O_p(1)$ and $X_n = o_p(1)$ to signify that the sequence of random variable X_n is bounded and converges to zero, respectively, as the sample size, n, goes to infinite.

2 A Model with Local Persistency

2.1 Locally Persistent Process Without Drift

The time series that we consider is the following process

$$y_i = \alpha y_{i-1} + u_i, \alpha = e^{\frac{c}{n^d}} \sim 1 + \frac{c}{n^d}, i = 1, \cdots\cdots, n \tag{2}$$

where the coefficient "α" in the autoregression is near unity and measures the persistency in time series y_i. We allow the errors u_i to be a general covariance stationary time series which satisfies an invariance principle.

It can be verified that by a re-parameterization ($m = n^d$) we may re-write the above time series in the format of a block local to unit root model which was first introduced by Phillips et al (2001). For more discussions on regularity assumptions and asymptotic properties of the above time series, see Phillips et al (2001).

The process provides a new form of persistent behavior when $0 < d < 1$. The above device provides a statistical model for what may be described as "locally persistent behavior" for macroeconomic time series. Many macroeconomic time series are now well known to display a form of persistence whereby economic shocks have long-run effects. However, it is possible that shocks may affect an economy for a long period of time but not forever. In other words, the effects of a shock may be highly persistent over a certain range (the range of persistent behavior), but then may begin to disappear outside this range. In the above model, the largest autoregressive root of time series y_i is close to unity and thus persistency can be found in y_i. On the other hand, the series evolves over time in such a way that there is persistency over a range of time (of order $O(n^d)$, compared to the full sample range n), but the effect of shocks will eventurelly disappear over time horizon longer than order $O(n^d)$. The region of persistent behavior may constitute a 'little infinity' relative to the full sample. Since there is persistent memory within a time horizon of order $O(n^d)$, but there is only short memory over longer periods, we call this type of memory "local persistence" or "temporal persistence". For this reason, we call the above process a Locally Persistent process with persistent parameter d.

We are especially interested in the case that $0 < d < 1$. In this case, the process has autoregressive coefficient near unity $\alpha = e^{c/n^d}, c < 0$ but it is not the conventional stationary or unit root process. It is a locally persistent process. In particular, $y_{[nr]} = O(n^{d/2})$, implying that the process will ultimately diverge at rate $n^{d/2}$ as $n \to \infty$.

However, the model does include traditional stationary process and the unit-root type persistency as two special extreme cases. In particular,

(i) When $d = 1$, it reduces to the traditional near-integrated processes and has the conventional unit-root type persistency. In particular, shocks has permanent effects, with $y_{[nr]}$ diverging at rate $n^{1/2}$. See, inter alia, Phillips (1988), for properties of this kind of process

(ii) When $d = 0$, the process becomes standard stationary process.

Locally persistent processes are not covariance-stationary and, as we will see soon, they may be used to model the dynamics of economic time series that display persistence as well as transitory shocks.

2.2 Locally Persistent Process With A Deterministic Trend

The locally persistent process can be extended to include a deterministic time trend. Such an extension is important because many economic time series display tendency of growth. We may consider a locally persistent process y_i^{τ} with trend component

$$y_i^{\tau} = \tau_i + y_i; y_i = ay_{i-1} + u_i, a \sim 1 + \frac{c}{n^d}, i = 1, \cdots\cdots, n. \tag{3}$$

where τ_i is a deterministic trend, the leading case being a linear time trend where $\tau_i = \varphi_o + \varphi t = \varphi_y' \Upsilon_i$. The stochastic part represented by Eq. (3) corresponds to (2), a locally persistent process without trend.

Note that the trend coefficients are unknown and thus, in practice, appropriate detrending is needed. We may estimate y_i from the residuals of the following detrending regression

$$y_i^{\tau} = \widehat{\varphi}_y' \Upsilon_i + \widehat{y}_i \tag{4}$$

where $\widehat{\varphi}_y$ is the least squares estimator of φ_y. The detrended time series $\widehat{y}_i$ has properties similar to the process with no drift y_i.

2.3 Local Persistency versus Long Memory

A related but different model is the long-memory, or fractional integrated process with order of integration equal to d[3], that is, FI(d) with $d \in (0, 1)$. Both the locally persistent process that we consider in this paper and the conventional fractional integrated process

[3] We stress that although we have used the same notation (d), the parameter of fractional integration and local persistency are unrelated.

are between the conventional covariance stationary process and unit root process. However, these two process have important differences. In particular, the fractionally integrated process (FI(d)) is more appropriate to capture long-range dependence, and our local persistence process (LP(d)) captures regional persistence. We illustrate below the differences in terms of impulse response functions

2.3.1 The Behavior of the Impulse Response Function

An impulse response function traces the effect of a shock in the innovation u_i on current and future values of the endogenous variable y_i . If the process is stationary, $d = 0$, then its impulse response will converge to zero as the response horizon k increases and we say that the shocks are transitory. On the other hand, when the process y_i has a unit root the impulse response never converges to zero. Thus, when the process is a random walk we say that the shocks are permanent implying that an initial shock never dies out. As an illustration, consider the following models:

Model 1: $y_i = \alpha y_{i-1} + u_i$, $u_i \sim iid$ and $|\alpha| \leq 1$.

Model 2: $(1 - L)^d (y_i - \mu) = u_i$, $u_i \sim iid$ and $\alpha = 1$.

Model 3: $y_i = \alpha y_{i-1} + u_i$, $u_i \sim iid$, $\alpha = e^{-1/n^d}$.

In all these models we assume that u_i is an i.i.d sequence of innovations.

In Model 1, y_i is stationary when $|\alpha| < 1$. If the response horizon equals k, one can show that the k period impulse response $IR_k = \dfrac{\partial y_k}{\partial u_1} = \alpha^{k-1} \to 0$ as $k \to \infty$. Therefore, if y_i is stationary the shocks will be totally absorbed as k increases. Also notice that, according to model 1, the total impact of a unit innovation, $\sum\limits_{k=0}^{\infty} IR_k < \infty$. Now we consider Model 1 where y_i has a unit root, that is, $\alpha = 1$. In this random walk specification, it is well known that $IR_k = 1$ for any k. (If u_i is not an i.i.d. sequence, then the impulse response function may move up and down but with no convergence toward zero.) The shocks never vanish when there is a unit root and, more importantly, the total impact goes to infinity, that is, $\sum\limits_{k=0}^{\infty} IR_k = \infty$.

Model 2 represents a fractional white noise process. This process can be expressed as an infinite order moving average representation,

$$\mathbf{y}_i = \sum_{j=0}^{\infty} \mathbf{\Psi}_j \mathbf{u}_{i-j}$$

Therefore $IR_k = \dfrac{\partial y_k}{\partial u_1} = \Psi_k \approx 1/(k^{1-d})$ for $0 < d < 1$. So, the impact of the innovations vanishes in the long run, but vanishes slow. Also notice that since $0 <$

$1-d<1$, we have $\sum_{k=0}^{\infty} IR_k = \infty$ so that the total impact of a unit innovation is infinite which is similar to the result obtained in the unit root case.

Now, we analyze the behavior of the impulse response function locally persistent processes. Consider the standardized locally persistent process given in Model 3 with $0<d<1$. The k period impulse response is given by $IR_k = (e^{-1/n^d})^{k-1}$ and we can see that $IR_k \to 0$ if $k = O_p(n^{d+\epsilon})$ for any $\epsilon > 0$ ($IR_k \not\to 0$ if $k = O_p(n^d)$ or $o_p(n^d)$). Thus, the impulse response does not go to zero in relatively shorter period, but disappears in longer horizon. For any time period k that is proportional to the sample size n, $IR_k \to 0$. In this sense, we say that if the process is locally persistent, its impulse response eventually converges to zero and, therefore, the shocks are globally transitory. Moreover one can see that $\sum_{k=0}^{\infty} IR_k < \infty$ as $n \to \infty$ and, therefore, the impact of innovations dissipates faster when the process is locally persistent than when it is a fractional white noise. Moreover, the degree of persistency is determined by the parameter d: the larger d, the more persistent are the shocks and, therefore, we can affirm that shocks take much more time to die out when the process is locally persistent $(0<d<1)$ than when it is stationary. In the degenerate case of model (2) where $d=1$, the $k-$period impulse response function $\frac{\partial y_k}{\partial u_1} = \alpha^{k-1} = (e^{-1/n})^{k-1}$. In this case, the autoregressive coefficient converges to one at rate n which is the same rate by which the exponent $k-1$ goes to infinity. Thus, the coefficient is close enough to unity to avoid the impulse response function converging to zero, and therefore $\sum_{k=0}^{\infty} IR_k \to \infty$ as $n \to \infty$[4]. This is because that a nearly integrated process have same unit-root type of persistency, that is, the shocks are not transitory.

Overall, we may say that a locally persistent process and a fractionally integrated process are similar in the sense that they are sitting in between the stationary and unit root extremes and their impulse responses converge to zero. However, it is important to stress that the total impact of a innovation will never be less than infinite if the process is fractionally integrated and this represents an important difference between local persistence and long memory. In practice, it may be more appropriate to think at a mean-reverting economic variable as a process in which the total impact of a unit innovation is finite. For example, techonological innovations (shocks) might trigger a persistent economic growth, but it would be hard to believe that the total impact of such innovations on the GDP is going to persist forever. As another example, if one says that the real exchange rate (RER) is neither I(0) nor I(1), then the purchasing power parity (PPP) holds no matter whether RER is fractionally integrated or locally persistent. However, a complete parity reversion would not take place at a finite time

[4] Of course this is also true for any $c<0$.

period if real exchange rate is fractionally integrated since its impulse response function is decaying hyperbolically. On the other hand, full PPP reversion would occur in a finite time horizon if real exchange rate is locally persistent.

We have seen so far that the persistency parameter d is important to determine the extension of region of persistency of a locally persistent process. Hence, it turns out to be important to discuss estimation of d as well as testing related hypothesis. In the next two sections, we discuss estimation of d and propose a test for the null that the process y_i is stationary $(d = 0)$ against the alternative with local persistency.

3 Estimation of the Local-Persistence Parameter.

According to local persistence process, the extension of region of persistency is given by the magnitude of the parameter d. The greater the value of d, the longer the persistent range and the longer the persistent effect will last. Therefore, it turns out to be important to estimate the parameter d in order to identify the degree of local persistence of the stochastic process. In order to do so, without changing the level of persistency (magnitude of d), we need to standardize the localizing parameter. For convenience, we consider a standardized LP process, in which the localizing parameter, c, equals -1. Notice that $1 - \alpha = n^{-d}$, and after taking the logarithm , one obtains

$$d = -\frac{\ln(1-\alpha)}{\ln(n)} \tag{5}$$

Following Phillips et al (2001), after standardization, we have that:

$$n^{\frac{1}{2}+\frac{d}{2}}(\widehat{\alpha} - \alpha) \Rightarrow \xi = N(0, 2). \tag{6}$$

i.e.

$$n^{\frac{1}{2}-\frac{d}{2}}[n^d(\widehat{\alpha} - 1) + 1] \Rightarrow \xi \tag{7}$$

where

$$\widehat{\alpha} = \widehat{\alpha}_{OLS} - \frac{n\widehat{\lambda}}{\sum y_{i-1}^2}$$

Therefore, $\widehat{a}$ is made up of two components. The first one corresponds to the usual least-square estimator of a. The second one is a nonparametric correction that uses the consistent estimator of the one sided long run covariance parameter, $\widehat{\lambda}$.[5] The non-parametric correction is needed whenever we have a non i.i.d. innovation sequence.

[5] $\widehat{\lambda} = \frac{1}{2}(\widehat{\sigma}_\mu^2 - \widehat{\omega}_\mu^2)$, where $\widehat{\sigma}_\mu^2$ is a consistent estimator of the variance of μ_i and $\widehat{\omega}_\mu^2$ is a consistent estimatior of the long-run variance of μ_i. In this paper, we consistently estimate ω_μ^2 by using nonparametric kernel smoothing.

When the innovation sequence $\{u_i\}$ is independent and identically distributed, we have $\lambda = 0$.

The above result implies that

$$n^d(1-\widehat{\alpha}) \xrightarrow{P} 1 \qquad or \;\; \ln[n^d(1-\widehat{\alpha})] \xrightarrow{P} 0 \tag{8}$$

Hence, one can propose the following consistent estimator for d :

$$\begin{aligned} \widehat{d} &= -\frac{\ln(1-\widehat{\alpha})}{\ln(n)} \\ &= -\frac{\ln[n^d(1-\widehat{\alpha})] - d\ln(n)}{\ln(n)} \\ &= d - \frac{\ln[n^d(1-\widehat{\alpha})]}{\ln(n)} \\ &\to d \end{aligned} \tag{9}$$

4 Testing the Null Hypothesis of Stationarity against Local Persistency

In this section, using the proposed models (2) and (3), we construct a test for the null hypothesis of covariance stationarity, $H_o : d = 0$, against the alternative of local persistency, that is, $H_a : 1 \geq d > 0$. Notice that under the null, the order of magnitude of the partial sum process $\sum_{i=1}^{k} y_i$ should be proportional to $(k^{1/2})$ (although y_i may have high variance, it is not large in order of magnitude and can be normalized). Under mild conditions $n^{-1/2}\sum_{i=1}^{[nr]} y_i$ $(0 < r < 1)$ satisfies an invariance principle. On the other hand, if the time series is locally persistent as described by (2), the cumulated sum process $\sum_{i=1}^{k} y_i$ diverges to ∞ more rapidly than rate $k^{1/2}$. This observation suggests that it is possible to design a test by looking at the order of magnitude of the partial sum process.

We consider the following quantity as a measurement of the magnitude of the cumulated sum

$$\underset{1\leq v\leq n}{Max}\frac{1}{\sqrt{n}}\left|\sum_{i=1}^{v} y_i - \frac{v}{n}\sum_{i=1}^{n} y_i\right|$$

Under H_0, the above quantity converges weakly to $\sup_{0\leq r\leq 1}\left|\widetilde{B}(r)\right|$, where $\widetilde{B}(r) = B(r) - rB(1)$ is a Brownian bridge which is tied down to the origin at the end of the

$[0,1]$ interval, with variance $\omega^2 =$ long-run variance of $y_i = \lim_{n\to\infty} \mathrm{E}\left(\frac{1}{\sqrt{n}}\sum_{i=1}^{n} y_i\right)^2$.
Under the alternative hypothesis, y_i is a locally persistent, it is easy to verify that the corresponding statistic has much larger order of magnitude, diverging to ∞ as $n \to \infty$.

Notice that in practical analysis the limiting distribution depends on the long-run variance parameter ω_y which is unknown and thus the above quantity can not be used directly. However, ω_y^2 can be consistently estimated using nonparametric kernel smoothing. We denote the estimator for ω_y^2 as $\widehat{\omega}_y^2$. We propose the following two statistic for testing the null hypothesis of stationarity or trend stationarity against local persistent nonstationarity

$$Q_n = \underset{1\le\upsilon\le n}{Max} \frac{1}{\sqrt{n}} \frac{1}{\widehat{w}_y} \left| \sum_{i=1}^{\upsilon} y_i - \frac{\upsilon}{n} \sum_{i=1}^{n} y_i \right| \tag{10}$$

$$\widehat{Q}_n = \underset{1\le\upsilon\le n}{Max} \frac{1}{\sqrt{n}} \frac{1}{\widehat{w}_y} \left| \sum_{i=1}^{\upsilon} \widehat{y}_i - \frac{\upsilon}{n} \sum_{i=1}^{n} \widehat{y}_i \right| \tag{11}$$

where Q_n is the test statistic evaluated at the observable time series, y_i, and $\widehat{Q}_n$ is the test statistic evaluated at the detrended time series $\widehat{y}_i$.

Theorem 1: (asymptotic behavior of the test statistic Q_n under the null, $d = 0$) Let y_i be a process without a time trend (t) as defined in (2). Under H_o $(d = 0)$ and the assumption of Phillips et al. (2001),

$$\begin{aligned} Q_n &= \underset{1\le\upsilon\le n}{Max} \frac{1}{\sqrt{n}} \frac{1}{\widehat{w}_y} \left| \sum_{i=1}^{\upsilon} y_i - \frac{\upsilon}{n} \sum_{i=1}^{n} y_i \right| \\ &\Rightarrow \sup_{0\le r\le 1} |W(r) - rW(1)| \end{aligned} \tag{12}$$

Table II reproduces the critical values for the test statistic Q_n.

Table I: Upper Tail Critical Values for Q_n

Level of significance	0.1	0.05	0.01
Critical value	1.22	1.36	1.63

Theorem 2: (asymptotic behavior of the test statistic $\widehat{Q}_n$ under the null, $d = 0$). Let y_i be a process with a time trend (t) as defined in (3). Under H_o $(d = 0)$ and assumptions of Phillips et al. (2001),

$$
\begin{aligned}
\widehat{Q}_n &= \underset{1\le \upsilon \le n}{Max} \frac{1}{\sqrt{n}} \frac{1}{\widehat{w}_y} \left| \sum_{i=1}^{\upsilon} \widehat{y}_i - \frac{\upsilon}{n} \sum_{i=1}^{n} \widehat{y}_i \right| && (13)\\
&\Rightarrow \sup_{0 \le r \le 1} \left| W(r) - rW(1) + 6(1-r) \left\{ \frac{1}{2} W(1) - \int_0^1 W(s)ds \right\} \right|
\end{aligned}
$$

where $\widehat{y}_i$ is the detrended value of y_i.

In Theorem 1, the test statistic converges to a functional of Brownian bridge. Theorem 2, on the other hand, states that the test statistic $\widehat{Q}_n$ converges to the sup of the Brownian bridge plus a second term brought of a time trend t. Xiao (1999) calculated, via simulation, the critical values for the test statistic $\widehat{Q}_n$ which is reproduced in the table below.

Table II: Upper Tail Critical Values for $\widehat{Q}_n$

Level of Significance	0.1	0.05	0.01
Critical value	0.827	0.901	1.041

It is critical that a statistical test be able to discriminate between the null and the alternative in large sample. The following Theorem gives properties of the tests under the alternative.

Theorem 3: (Consistency). Under the alternative hypothesis that $H_a : 0 < d \le 1$,

(i) $\frac{1}{\widehat{w}_y} \frac{1}{\sqrt{n}} \sum_{i=1}^{[nr]} y_i = O_p(\sqrt{\frac{n^d}{q}})$,

(ii) $\frac{1}{\widehat{w}_y} \frac{1}{\sqrt{n}} \sum_{i=1}^{[nr]} \widehat{y}_i = O_p(\sqrt{\frac{n^d}{q}})$,

(iii) Assuming that the bandwidth parameter $q = o_p(n^d)$, then Q_n (and $\widehat{Q}_n$) $\to \infty$, indicating that under the alternative hypothesis, the test statistic will reject the null with probability one.

Theorem 3 shows that if we choose $q = o_p(n^d)$, say, $q = \ln(n)$, the statistical test proposed in this section is consistent since Q_n and $\widehat{Q}_n$ diverge under the alternative hypothesis as $n \to \infty$.

4.1 Monte-Carlo Results

A Monte Carlo experiment was conducted to examine the finite performance of the test statistic $\widehat{Q}_n$ under H_o and H_a[6]. From the construction of $\widehat{Q}_n$ we know that such statistics depends on the sample size n, the parameter of persistency d, and the bandwidth parameter q that is used to calculate $\widehat{w}_y^2$. Consequently, we paid special attention to the effects of n, d, and, q on the performance of this test. We considered the following sample sizes: $n = 200, 300, 400$, and 700. These sample sizes represent the most relevant range of sample sizes in many empirical analyses. Four bandwidth choices were considered, the first two bandwidth values are small and fixed, $q_1 = 1$, $q_2 = 2$, while the third bandwidth value $q_3 = \ln(n)$ is function of the sample size and are increasing with n. We used four values for the persistency parameter: $d = 0.2, 0.5, 0.8, 1.0$. The first one corresponds to a process with local persistence but still close to stationarity, the second and third values represent processes with local persistence. The degenerate case, $d = 1$, represents near integration and this process is supposed to diverge to infinity at the same rate as a process with unit root, i.e., $O(n^{1/2})$. All experiments used 10,000 replications. For the Kernel function, following Kwiatkowski et al. (1992), we used the Bartlett window $k(x) = 1 - |x|$, so that the nonnegativity of $\widehat{w}_y^2$ was guaranteed.

4.1.1 Power of Test

The data were generated from $y_i^\tau = \tau_i + y_i$, where τ_i is a linear trend $y_i = (1 - \frac{1}{n^d})y_{i-1} + u_i$, with $u_i \equiv i.i.d.N(0,1)$. In each replication, we used the detrended value of y_i^τ, $\widehat{y}_i$ to calculate the value of the test statistic $\widehat{Q}_n$[7]. Theorem 3 predicts that we will reject the null hypothesis with probability one when the sample size goes to infinity and H_1 is true. For the four values of the local-persistence parameter d, the tables below confirm what the theory predicts, that is, for any $0 < d \leq 1$, the probability of rejecting H_o increases toward unity as the sample size increases. In particular, the test exhibits low power when the process is near stationary, that is, when d and the sample size are small ($d = 0.2$ and $n = 200$, for example.) . However, the power of the test increases significantly whenever the presence of local persistence becomes more evident (i.e., when d increases). One can also see that the power is reduced as the bandwidth parameter q increases because, as showed by theorem 3, the power of our test depends upon n^d/q. In other words, a large q will reduce the power, whereas a large n and a large d will increase the power. All this is confirmed by the Monte-Carlo results presented below.

[6] We choose $\widehat{Q}_n$ because the specification with linear trend represents the leading case in many applied works.

[7] We also considered cases where u_t displays serial correlation. In this case we modelled $u_t = \alpha u_{t-1} + e_t$ where $e_t = N(0,1)$ and $|\alpha| < 1$. The conclusion on power and size of the test is still the same and these results are available upon request.

Table III: Power of Test, 5% level.

Bandwidth Parameter $= q_1 = 1$				
	Sample Size (n)			
Local Persistence Parameter	$n = 200$	$n = 300$	$n = 400$	$n = 700$
$d = 0.2$	0.4911	0.5851	0.6576	0.7661
$d = 0.5$	0.9751	0.9941	0.9984	0.9999
$d = 0.8$	0.9968	0.9995	0.9998	0.9999
$d = 1$	0.9969	0.9996	0.9999	0.9999

Table IV: Power of Test, 5% level.

Bandwidth Parameter $= q_2 = 2$				
	Sample Size (n)			
Local Persistence Parameter	$n = 200$	$n = 300$	$n = 400$	$n = 700$
$d = 0.2$	0.2876	0.3763	0.4399	0.5490
$d = 0.5$	0.8998	0.9657	0.9838	0.9986
$d = 0.8$	0.9755	0.9958	0.9991	0.9999
$d = 1$	0.9804	0.9969	0.9996	0.9999

Table V: Power of Test, 5% level.

Bandwidth Parameter $= q = \ln(n)$				
	Sample Size (n)			
Local Persistence Parameter	$n = 200$	$n = 300$	$n = 400$	$n = 700$
$d = 0.2$	0.0819	0.0985	0.1296	0.1524
$d = 0.5$	0.5649	0.6588	0.7759	0.8857
$d = 0.8$	0.8228	0.9007	0.9581	0.9923
$d = 1$	0.8536	0.9208	0.9685	0.9942

4.1.2 Size of Test

We next examined the size properties of $\widehat{Q}_n$ under the null hypothesis. For this purpose, the data were generated from $y_i^\tau = \tau_i + y_i$, where τ_i is a linear trend $y_i = \alpha y_{i-1} + u_i$, with $u_i \equiv i.i.d.N(0, 1)$. In this model, α is not assumed to be local to unity and, therefore, it will not converge to unity as the sample size increases. Thus, if we choose an appropriate bandwidth parameter q, we could expect that the size of test would converge to the nominal size as the sample size increases. Notice, however, that the bandwidth parameter q corresponds to the number of lags used to calculate $\widehat{w}_y^2$. Intuitively, for $\alpha > 0$, the larger α is, the longer lags we need. In the case that $\alpha = 0$, y_i is an independent sequence and the long-run variance of y_i equals the variance of y_i. Thus, we expect that for small α a small bandwidth parameter would be more appropriate than a large one. On the other hand, if α is large then we need to increase q in order to account for the existence of serial correlation in y_i. Once more, the Monte-Carlo confirms the theory: small size distortions are obtained when the process y_i is not highly correlated and we use a small truncation parameter. When the autocorrelation is too severe, we can still reduce the size distortion by using a sample dependent bandwidth, like q_3,but a large value of q will always reduces the power of the test and a trade-off has to be made.

Table VI: Size of Test, 5% Level

α	n	q_1	q_2	q_3
0.0	200	0.0289	0.0257	0.0225
	300	0.0334	0.0327	0.0299
	400	0.0388	0.0377	0.0354
	700	0.0411	0.0406	0.0384
0.2	200	0.0692	0.0481	0.0276
	300	0.0837	0.0597	0.0361
	400	0.0918	0.0641	0.0412
	700	0.1016	0.0727	0.0457
0.5	200	0.2651	0.1480	0.0467
	300	0.298	0.1691	0.0551
	400	0.3235	0.1979	0.0645
	700	0.3467	0.2083	0.0694
0.7	200	0.5798	0.3556	0.1055
	300	0.6261	0.4080	0.1077
	400	0.6608	0.4424	0.1304
	700	0.7075	0.4829	0.1308

5 Local Persistency in Economic Time Series

In this section, we investigate the presence of local persistency in economic time series. Since information on the dynamic of the shocks affecting the real side of the economy is very important to policy makers,we pay particular attention to three main real variables of the US economy: real exchange rate (RER), real interest rate (RIR) and real GNP (RGNP). In other words, we want to investigate whether the effects of shocks on these variables die out slowly (local persistence process), rapidly (ergodic stationary process) or never dissipate (near integrated or unit root process).

We used monthly data of three bilateral real exchange rates: France-USA (RER(Fra-

US)) Germany-USA (RER(Ger-US)), and the United Kingdom and the United States (RER(UK-US)). The data on the nominal exchange rate (end of period) and price level (Consumer Price Index) are collected from the International Financial Statistics CD-Rom, which is made by the International Monetary Fund (IMF). The sample covers the Post-Bretton Woods period that runs from April 1973 to March 2001, which totalizes 336 observations. Real exchange rates are in logarithm form.

The data on RGNP were collected from the U.S. Department of Commerce, Bureau of Economic Analysis. The data are measured in billions of fixed 1996 Dollars and are seasonally adjusted annual values, with first observation corresponding to the first quarter of 1967, which totalizes 141 observations. As with RER, RGNP is in logarithm form. As for the real interest rate, we used the nominal interest rate with 12-month and 3-month maturity together with the 12-month and 3-month ex-post inflation rates to calculate the real interest rates with 12-month (RIR-12m) and 3-month (RIR-3m) maturity. All the four series are monthly observed with first observation corresponding to the first month of 1967, which totalizes 401 observations [8]. The timing of the data is as follows: A January interest rate uses the end-of-January m-month bill rate data. A monthly observation of the m-month inflation is calculated taking into account m observations ahead. For example, A January observation of the 12-month inflation rate in the year i is calculated from the January CPI data in the year i to the January CPI data in the year $i + 1$.

Figures 1, 2 and 3 show graphs of RER, RIR and RGNP. The series of RER and RIR are centered with respect to their sample means whereas RGNP is showed in detrended values. One can see that all the variables display wide fluctuations, but there seems to be a mean (trend) reversion in all cases. Therefore, we could expect unit root test to reject the null hypothesis of a unit root for these cases.

However, as suggested by past studies, this visual impression of mean reversion (or trend reversion) has been hard to establish statistically using traditional unit root tests. Table VII shows the results of the ADF test[9]. Unlike the visual evidence, we cannot reject the unit root hypothesis at 5% level of significance for the series of real exchange rate and real interest rate. Table VIII also show that the ADF test rejects the null hypothesis of unit root for the series of RGNP, which seems to suggest that the RGNP is trend stationary (TS). Trend stationarity of the RGNP has been previously reported in the literature by Diebold and Senhadji (1996) and Cheung and Chinn (1997).

[8] CPI: We have used CPI data- all urbans and non-seasonally adjusted index - collected from Board of Governors of the Federal Reserve System, http://www.stls.frb.org/fred/

Three-month and twelve-month Treasury Bill Rate: Board of Governors of the Federal Reserve System, http://www.stls.frb.org/fred/

[9] We used the same lag choice for the ADF and DF-GLS tests, that is, the choice based on the Modified Information Criteria (MIC) suggested by Perron and Ng (2001). The main advantage of this criteria is that it imposes the null hypothesis of unit root into the objective function used to calculate the optimal lag.

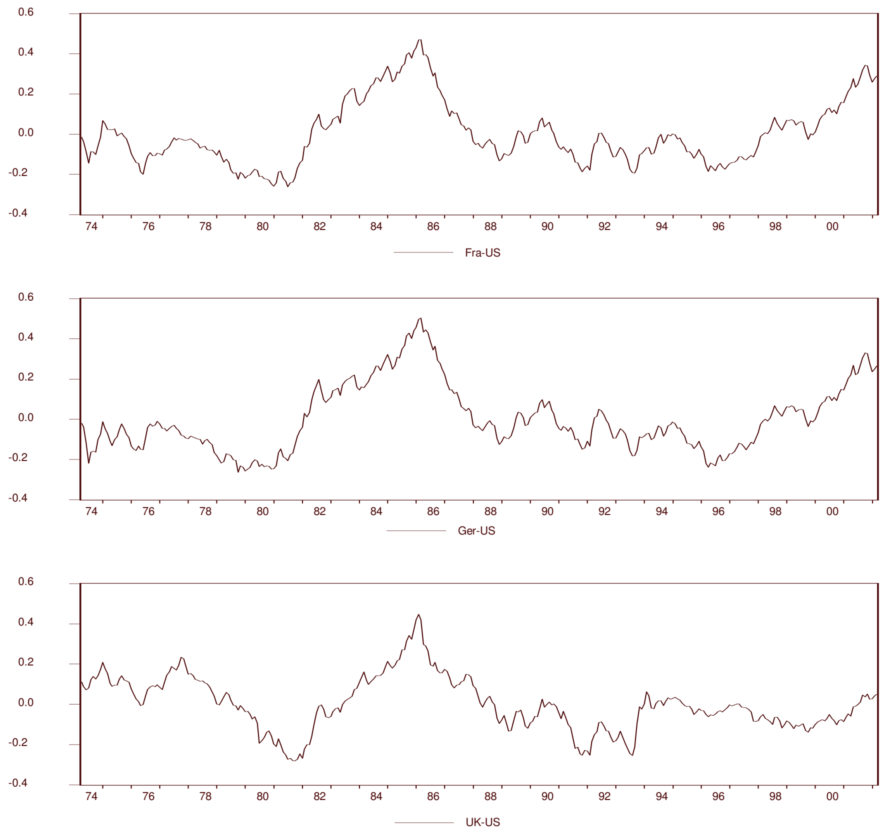

Figure 1: Real Exchange Rates (centered)

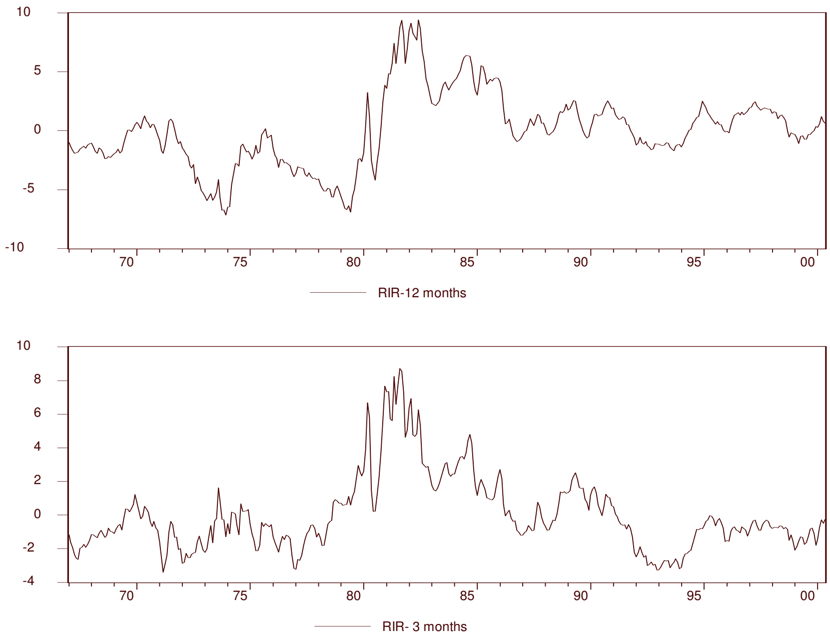

Figure 2: Real Interest Rates (centered)

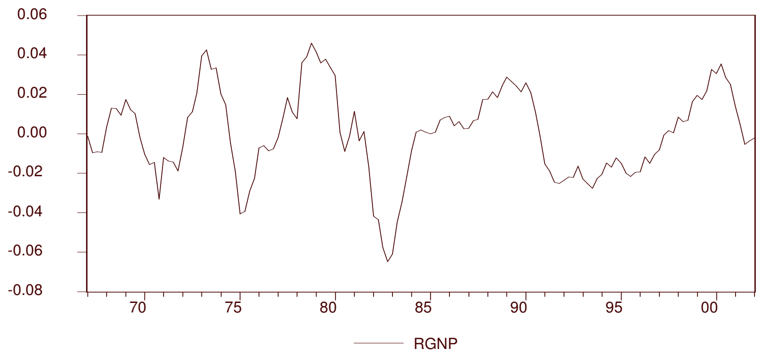

Figure 3: Real GNP (detrended)

Nonetheless, it is important to mention that the rejection of the null hypothesis of unit root does not necessarily imply that the process is ergodic stationary, for instance, it can also be locally persistent.

Another interesting aspect displayed in Table VII is that most of the series have roots near unity and, as documented by Campbell and Perron (1991) and Dejong et. al. (1992), near unity roots may explain the failure to reject the unit root null in the ADF test . Since processes with high degree of local persistence have roots too close to unity, we should employ a more powerful test to reject the null hypothesis of unit root. Elliot et al (1996) introduced a modified unit root test (DF-GLS) that has better power when the AR coefficient is close to unity. Table VII shows the results from the DF-GLS test with the notation '*', '**', and '***' indicating that the null of unit root is rejected at 10%, 5% and 1% level of significance. By using the DF-GLS test, we reject the null hypothesis of unit root for all variables of our sample.

Table VII: Unit Root Tests

Series	Specification	Lags	ADF	$\widehat{\alpha}$	DF-GLS
RER (Fra-US)	Intercept	5	-1.85	0.98	-1.84**
RER (Ger-US)	Intercept	8	-1.77	0.99	-1.74**
RER (UK-US)	Intercept	6	-2.45	0.98	-1.89**
RIR-3m	Intercept	8	-2.65*	0.97	-2.04**
RIR-12m	Intercept	9	-2.13	0.98	-2.44**
RGNP	Trend	4	-4.24**	0.96	-2.95**

In order to know whether the shocks die out slowly or rapidly, we recall that rejecting the null of unit root does not imply to say that the process is ergodic stationary. For example, if a time series display local persistence, then the impulse response will converge to zero, but the shocks will take more time to die out. For this reason, we test covariance stationarity of these series.

Table VIII reports the results for test of the null $H_o : d = 0$ against the alternative $H_1 : 0 < d \leq 1$, as well as point estimates of the local persistence parameter, d. We used the sample dependent truncation-lag $q = [\ln(n)]$, where [.] signifies an integer number. Again, the notation '*', '**', and '***' suggest that the null hypothesis, $d = 0$, is rejected at 10%, 5% and 1% level of significance, respectively. First, we notice that the results reported in Table X indicate that the data uniformly reject the stationarity null hypothesis, i.e. $d = 0$ against the alternative $0 < d \leq 1$. In addition, all the series have an estimated local persistence parameter, d, different from zero. Combining this result with the previous evidence in Table VII, our empirical analysis indicate that these time series is sitting between the conventional stationary and the unit root processes, supporting the existence of local persistency in US time series of real exchange rates, real interest rate and real GNP.

Table VIII: Results from Local Persistency Analysis

Series	$\widehat{d}$	Model	$H_o : d = 0$
RER(Fra-US)	0.80	Intercept	1.54**
RER(Ger-US)	0.77	Intercept	1.68**
RER(UK-US)	0.68	Intercept	1.87**
RIR-3m	0.56	Intercept	1.40**
RIR-12m	0.58	Intercept	2.58**
RGNP	0.51	Trend	0.92**

In sum, the existence of local persistence in the time series studied in this paper implies that shocks affecting RGNP, RIR and RER are long lasting, but the form of persistence may be different from the one suggested by a unit root and fractionally integrated process. In particular, the finding that RGNP displays local persistence reveals an important fact already mentioned in Cochrane (1988): trend reversion occurs over a time horizon characteristic of business cycle (several years at least), meaning that output fluctuations are highly persistent over certain range of time, but less persistent results are found around longer horizons. If we apply the measure of fluctuations suggeted by Cochrane (1988), we would obtain evidence against a random walk since local persistence is less persistent than a random walk process, but this does not imply that RGNP is trend stationary as suggested by Cochrane (1988). Our results suggest that the total impact of an unit innovation in RGNP is finite, which implies that a shock today is not able to affect forecasts of RGNP into the infinite future, although it may affect forecasts for a long time. Long-lasting innovations displayed by a local persitent process may be mixed up with permanent shocks if ones employs unit root tests without power against local persistency. In other words, if we use conventional ADF unit root tests, we will rarely reject the null of unit root due the low power of those tests to local persistency, which may wrongly suggest that shocks affecting RGNP are permanent. Using fractional integration models to capture the phenomenon of transitory shocks in RGNP is not appropriate either, since its impulse response function would decay only hyperbolically: the total impact of a unit innovation would be infinite and, consequently, shocks today would be able to affect forecasts into a infinite future. We believe that locally persistent process provides a useful alternative to the traditional unit root and trend stationary models, and is a useful complement to the fractional integrated model.

6 Conclusion

We study local persistency of macroeconomic time series. To capture the dynamic of locally persistency time series, we use a block local to unity model. We have proposed statistical tests for the null hypothesis of stationarity (or trend stationarity) against local persistency. The test statistics converge to nonstandard limiting distributions that are functions of Brownian motions, involving higher order Brownian bridges. Tables of critical values are provided based on the asymptotic null distributions and a Monte Carlo experiment was conducted to examine the finite performance of these test, with special emphasis to the study of the finite sample size and power. The test is applied to several important variables of the US economy: real GNP, real interest rates, and real exchange rates. Our results suggest that these macroeconomic time series may be locally persistent and, therefore, display a pattern of temporal dependence that is different from the one generated by a traditional unit root and fractionally integrated process.

7 Appendix

Theorems 1 and 2 are properties under the stationarity null and are proven as in Xiao (1999).

Proof of Theorem 3.

For the estimation of w_y^2, we consider the estimator

$\widehat{w}_y^2 = \sum_{h=-q}^{q} (1 - \frac{|h|}{q})\widehat{\gamma}(h)$

where $\widehat{\gamma}(h) = \frac{1}{n} \sum_{i=1}^{n-|h|} \widehat{y}_i \widehat{y}_{i+h},$ It is well known that under H_1, $\widehat{\gamma}(h) = O_p(n^d)$ and consequently $\widehat{w}_y^2 = O_p(n^d q)$. Under H_1, it can verified that $\dfrac{1}{\sqrt{n}} \sum_{i=1}^{[nr]} \widehat{y}_i = O_p(n^d)$.

Thus,

$\frac{1}{\widehat{w}_y} \dfrac{1}{\sqrt{n}} \sum_{i=1}^{[nr]} \widehat{y}_i = O_p(\frac{n^d}{\sqrt{n^d q}}) = O_p(\sqrt{\frac{n^d}{q}})$. Given that $q = o_p(n^d)$, we get a consistent test, that is, $\widehat{Q}_n \to \infty$ as $n \to \infty$.

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